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Solution of Time Constrained Vehicle Routing Problems using Multi-Objective Hybrid Genetic Algorithm

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***Abstract*— Vehicle Routing Problem with Time windows (VRPTW) is an example of scheduling in constrained environment. It is a well known NP hard combinatorial scheduling optimization problem in which minimum number of routes have to be determined to serve all the customers within their specified time windows. So far different analytic and heuristic approaches have been tried to solve such problems. In this paper we proposed an algorithm which incorporates a new local search technique with genetic algorithm approach to solve time constrained vehicle routing and scheduling problems in various scenarios.**

Keywords- Vehicle routing problem, genetic algorithm, heuristics based search techniques

I. INTRODUCTION

Scheduling and routing problems have attracted considerable attention in recent years due to their wide applicability and importance in determining efficient distribution strategies to reduce operational cost in transportation logistics. VRPTW is an extension of the Vehicle Routing Problems (VRP) arising in transportation logistics that usually involve scheduling in constrained environment.

In VRPTW, a set of K identical vehicles with fixed and identical capacity Q is to be routed from a central depot to a set of N geographically scattered customers which have varying demands d_i and pre-defined time windows $[a_i, b_i]$ where $i \varepsilon N$. Vehicles arriving later than the latest arrival times (i.e. after b_i) are penalized while those that reach the customer earlier than the specified earliest arrival time (i.e. before the a_i) incur waiting time w_i until service is possible. This penalizes the management either in the direct waiting cost or the increased number of vehicles to be used. This type of time window constraint is known as a hard time window.

The objective of VRPTW is to service all the customers as per their requirement while minimizing the number of vehicles required as well as the total travel distance of all the vehicles used without violating capacity constraints of the vehicles and the customer's time window requirement such that each customer is visited in any way once and only once by one of the vehicles. All the routes are to start and ultimately end at the depot. Figure 1 shows a graphical model of VRPTW and its solution.

Routing and scheduling problems arise in a wide range of practical decision making situations. VRPTW arises in retail distribution, school bus/taxi scheduling, waste collection, courier/mail delivery/pickup, and airline/railway fleet routing etc. VRPTW is NP-hard. It has been extensively investigated in recent years using analytic optimization techniques, heuristics and meta-heuristics approaches.

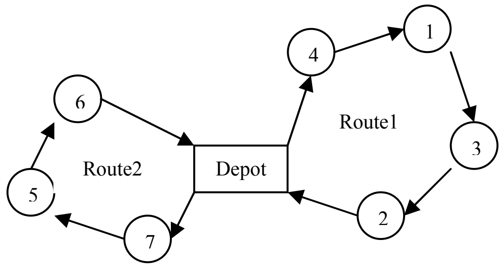

Figure 1. Typical output for VRPTW

The early work on VRPTW can be broadly divided into two categories: exact optimization and heuristic algorithms. Using exact optimization techniques, Kohl et al. [11], Larsen [12] and Chabrier [4] obtained significant improvements in Solomon's benchmark problem instances. Survey of the VRPTW literature by heuristics and meta-heuristics approaches has been given by Bräysy et al. [3] and Minocha et al. [14]. Cordeau et al. [5] and Rochat et al. [16] tried to solve these problems using tabu search whereas Gambardella et al. [7] considered ant colony optimization approach. Shaw [18] applied large neighborhood search (LNS). This was extended by Ropke et al. [17] as Adaptive-LNS approach to solve VRPTW problems. Homberger et al. [9] proposed parallelization of a two-phase metaheuristic technique for solving VRPTW. A complete survey of the VRPTW literature has been given by Cordeau et al. [6] which includes both the categories.

The Genetic Algorithm (GA) approach was proposed by Holland [8] in 1975. It is an adaptive heuristic search method that mimics evolution through natural selection. It works by combining selection, crossover and mutation operations of genes. The selection procedure drives the population toward a better solution while crossover uses genes of selected parents to produce new offsprings that form the next generation. Mutation is used to escape from local minima. The genetic algorithm approach has now become popular as it helps in finding reasonably good solutions for complex mathematical problems, NP-hard problems like VRP.

Blanton et al. [2] were the first to use GA approach to solve VRPTW. They hybridized GA approach with a greedy heuristic. A cluster-first, route-second method using genetic and local search optimization was used by Thangiah [22] and GENEROUS by Potvin et al. [15]. A multi-objective representation of VRPTW using pareto-ranking was used by

Ombuki et al [13]. Others such as Berger et al. [1], Tan et al. [21] and many more also used GA for solving VRPTW problems.

In this study we consider an alternative approach based on the merger of genetic algorithm approach with new local search heuristics for solving VRPTW problems. In section II we present our proposed hybrid of GA with heuristics based local search. Section III shows the results we obtained in solving some of the Solomon's benchmark problem by using proposed algorithm followed by conclusion in section IV. The work presented in this paper is an extension of the work presented and published in the proceedings of "International Conference on Electronics Computer Technology 2011".

II. HYBRID GENETIC ALGORITHM

Although GA perform well in global search, but they usually take long time to converge to the global optimal solution. On contrary local searches (valid in a small region of search space) are quick in finding an optimal solution. Thus to improve the efficiency of GA we try to incorporate local searches with them. We call these as hybridized GA.

After building the initial population, all individuals are evaluated according to the fitness criterias. The evolution continues with tournament selection, where good individuals are selected for reproduction. Two best individuals are kept for next generation without going through genetic operations. Crossover and mutation are then applied to modify the selected individuals to form a new feasible generation. To further improve the individuals, local search heuristics are applied. We generate a random number *r* between 0 and 1, if *r* is less than 0.8; one of the local search algorithms is then executed, otherwise no local search algorithm executed. The Process is continued iteratively till the best solution does not change for a specified number of generations or till an overall specified number of generations have been performed. The best solution is taken as the desired optimal solution.

The working of the proposed algorithm is summarized in the flowchart is shown in Figure 2.

A. Chromosome and Individual Representation

The representation of the GA chromosome in the present work is very simple. Each customer has an unique integer identifier *i*, where $i \varepsilon N$. An individual, which is a collection of chromosomes, represents a complete routing solution. Each chromosome represents a route, which is variable in length, contains a sequence of customers in the order in which they are visited by the vehicle. A different vehicle is needed to serve every chromosome of the individual. Every individual and every route must be feasible, in terms of capacity and time window constraints. The central depot is not considered in this representation, because all routes necessarily start and end in it. Figure 3 represents a complete routing solution for a problem instance with 25 customers, consisting of 3 routes which are served by 3 vehicles; genetically we call it as 3 chromosomes and complete solution as individual.

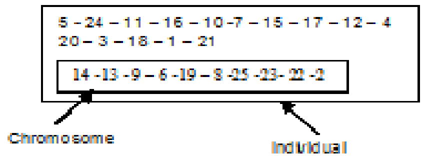

Figure 3. An individual with 3 chromosomes/routes.

B. Initial Population

An initial population is built such that each solution is a feasible candidate solution i.e. every individual and every chromosome/route in the population satisfies time window and capacity constraints. We first generate a feasible solution using Push Forward Insertion Heuristics (PFIH) first introduced by Solomon [19]. This method has been frequently used in literature. Details of this method are available in Thangiah [22]. Rest of the solutions of initial population is generated by selecting the customers in a random manner and inserting them in an existing route, if one exists, otherwise a new route is created. Any customer that violates any constraint is deleted and a new route is added to serve the customer. This process is repeated until all the customers get served and a feasible initial population has been generated.

C. Fitness

As soon as all the individuals have been created, they are ranked as per their fitness. In this study three fitness criteria have been used one by one:-

1) Distance Traveled and Number of Routes (DR): In this case we minimize the total distance traveled keeping at the same time the number of vehicles as low as possible as each route requires one vehicle to operate it.

2) Number of Routes and Distance traveled (RD): Same as (1) however with the priorities interchanged. First priority is to reduce the number of routes and second priority is to reduce total distance traveled.

3) Weighted Mean (WM): In this case we apply weighted sum method on total distance traveled and on the number of routes required to calculate the fitness of the individuals. This method requires adding the objective functions of the problem together using weighted coefficients for each individual. Thus we transformed VRPTW into a single-objective optimization problem where the fitness of an individual F(x) is evaluated as:

$$F(x) = \alpha \cdot V + \beta \cdot TD$$

$$TD = \sum_{i \in N} \sum_{j \in N} \sum_{k \in V} t_{ij} \cdot x_{ijk}$$

where α and β are weight coefficients associated with total number of vehicles, V and total distance traveled by vehicles, TD respectively. The weight values of the coefficients used here were established empirically and set at $\alpha = 100$ and $\beta = 0.001$.

D. Selection and Elitism

In selection, parents are selected for crossover. There are many methods proposed in the literature for this. In this study, an n-way tournament selection procedure has been used. Here n individuals are randomly selected and then the individual with highest fitness is declared as the winner. This process is repeated until the number of selected individuals equals to the number necessary for crossover. In this study, tournament size, i.e. n has been taken to be 3.

In the elitism process the good individuals are retained for reproduction. This ensures that the best solution obtained from the present population is copied unaltered in the next population. We replace the two worst individuals in the new population with the best two individuals of the parent population.

E. Crossover and Mutation

The classical single/double point crossover is not appropriate for scheduling problems like TSP or VRP because duplication and omission of vertices produce infeasible sequences in the offspring. Therefore in this study we have used route-exchange crossover. Once a pair of individuals is selected for crossover, efforts are made to exchange a route that has minimum number of nodes in each of the two individuals. To ensure that all individuals are feasible routing solutions after crossover, any duplication is deleted.

Mutation is necessary for inserting new characteristics that are not present in the current individuals. Without mutation the search gets limited to a very small area in the feasible region. In this study effort is made to transfer customers from route that has minimum number of nodes to other routes if possible to decrease the number of routes.

F. Local Search Heuristics

In this study we incorporate two new local search heuristics to search for better routing solutions of VRPTW. These searches are ‘Replacing Next Neighbour’ and ‘Reinserting Random Customer’.

1) Replacing Next Neighbour: In this local search heuristics after having selected an individual randomly, a node say C_j is randomly chosen on one of its routes and an effort is made to replace its next neighbour C_{j+1} by some alternative acceptable node, say C_k and then reinsert all the nodes from C_{j+1} onwards of this route in other routes. Necessary modifications are carried to generate a new feasible solution.

2) Reinserting Random Customer: This heuristic chooses a random customer from a randomly selected individual and tries to reinsert it in some other route. If possible we insert it and modify the existing solution else return the same individual.

III. Experimental Results and Comparison

In this section we summarize the results of the computational experiments performed by us using the proposed algorithms on a set of benchmark test problems selected from Solomon’s set of problems.

Solomon [19] generated a set of 56 problems which have been frequently used in the literature to assess and compare the performance of various algorithms developed for solving VRPTW problems. The problems vary in available fleet size, vehicle capacity, traveling time of vehicles, spatial and temporal distribution of customers to be served. The classes R1 and R2 have customers randomly distributed, while the classes C1 and C2 have customers clustered. The classes RC1 and RC2 contain a subset of customers randomly disposed and the other part clustered. Problem sets R1, C1 and RC1 have a short scheduling horizon and allow only a few customers per route (approximately 5 to 10). In contrast, the sets R2, C2 and RC2 have a long scheduling horizon permitting many customers (more than 30) to be serviced by the same vehicle. Larger problems have one hundred customers to be served. Smaller problems have been created out of these by considering only the first 25 or first 50 customers.

Each problem has been solved ten times using three different fitness criteria using proposed algorithms. In our present study we have chosen from these sets: 15 problems of 25 customers; 10 problems of 50 customers and 5 problems of 100 customers. The best and the worst results (fitness criteria wise) are listed in Table 1 for 25 node problems. Table 2 shows results for 50 node problems and Table 3 for 100 node problems. Following parameters have been used: Population Size = 100; Generation size = 1000; Crossover rate = 0.80; Mutation rate = 0.20.

Table 1, 2 and 3 present a summary of our results and compare them with the best-known routing solutions available in literature. Bold numbers in Table 1, 2 and 3 indicate that the obtained solutions are the same as the best-known or there is an improvement on the currently best known solution. The proposed algorithm has been coded in C++ language and implemented on a laptop having Intel(R) Core(TM) 2 Duo 2.0 GHz. Regarding the complexity of the algorithms it is of order $O(MN^2)$. Here M is the number of objectives and N is the total feasible solutions. This is due the fact that for each objective each feasible solution has to be evaluated and for ranking each of the N solutions are compared with each other.

The proposed algorithms have produced new improved results in RC201-RC208, R105 and R109 problems of 25 nodes with smaller number of vehicles but with slightly higher routing cost. Similarly for 50 node problems, C2 and R2 show some good solutions which need lesser vehicles, in all the three criteria’s. In 100 node problems, for R101, we obtained the best-known solution in RD and WM criterias. In 100 node problem for RC101, we obtained one solution in the Table 3 that have better distance scores than the best known solution. However, it needs more vehicles than the best-known solutions. For rest of the cases, almost all the results are within (10%) of the best-known, in some cases

TABLE I. COMPARISON OF BEST KNOWN RESULTS WITH THE RESULTS GENERATED BY PROPOSED GENETIC ALGORITHMS FOR SOLOMON'S 25 CUSTOMERS SET PROBLEM

Problem	**DR**		**RD**		**WM**		**Best Known [Ref.]**
	Best	***Worst***	***Best***	***Worst***	***Best***	***Worst***	
C201	2/ 219.10	2/ 237.15	2/ 215.54	2/ 282.25	2/ 215.54	2/ 237.15	**2/ 214.7 [11]**
R101	8/ 618.33	8/ 649.07	8/ 618.33	8/ 644.68	8/ 618.33	8/ 656.49	**8/ 617.1 [11]**
R102	7/ 580.05	7/ 675.54	7/ 579.94	7/ 671.91	7/ 580.20	7/ 640.72	**7/ 547.1 [11]**
R105	6/ 531.80	6/ 616.00	**5/ 559.84**	6/ 657.10	**5/ 588.34**	6/ 598.79	**6/ 530.5 [11]**
R109	5/ 490.03	5/ 641.16	**4/ 517.29**	6/ 559.10	5/ 459.75	5/ 608.68	**5/ 441.3 [11]**
RC105	4/ 457.56	5/ 515.82	4/ 457.56	5/ 554.47	4/ 460.91	5/ 571.98	**4/ 411.3 [11]**
RC106	3/ 363.17	4/ 458.16	3/ 360.98	4/ 469.48	3/ 361.51	4/ 461.42	**3/ 345.5 [11]**
RC201	**2/ 509.46**	2/ 656.83	**2/ 509.46**	2/ 670.59	**2/ 519.35**	2/ 654.69	**3/ 360.2 [12]**
RC202	**2/ 480.24**	2/ 652.62	**2/ 504.03**	2/ 617.28	**2/ 513.23**	2/ 663.36	**3/ 338.0 [10]**
RC203	**2/ 425.61**	2/ 557.07	**2/ 435.48**	2/ 544.11	**2/ 458.86**	2/ 575.30	**3/ 326.9 [4]**
RC204	**2/ 407.86**	2/ 585.45	**2/ 402.31**	2/ 590.51	**2/ 421.24**	2/ 501.35	**3/ 299.7 [4]**
RC205	**2/ 459.57**	2/ 662.42	**2/ 567.16**	2/ 697.56	**2/ 506.57**	2/ 624.75	**3/ 338.0 [12]**
RC206	**1/ 594.92** **2/ 501.62**	1/ 630.47	**1/ 594.92** **2/ 495.73**	1/ 630.47	**1/ 649.04** **2/ 518.72**	1/ 682.91	**3/ 324.0 [10]**
RC207	**2/ 428.78**	2/ 619.22	**2/ 424.43**	2/ 600.88	**2/ 435.51**	2/ 574.74	**3/ 298.3 [10]**
RC208	**1/ 431.07**	1/ 507.23	**1/ 431.07**	1/ 527.35	**1/ 419.26**	1/ 494.63	**2/ 269.1 [4]**

TABLE 2: COMPARISON OF BEST KNOWN RESULTS WITH THE RESULTS GENERATED BY PROPOSED GENETIC ALGORITHMS FOR SOLOMON'S 50 CUSTOMERS SET PROBLEM.

Problem	**DR**		**RD**		**WM**		**Best Known [Ref.]**
	Best	***Worst***	***Best***	***Worst***	***Best***	***Worst***	
C101	5/ 363.25	6/ 513.01	5/ 388.77	6/ 544.31	5/ 363.25	6/ 573.77	**5/ 362.5 [11]**
C201	**2/ 501.13**	2/ 561.43	**2/ 515.81**	2/561.43	**2/ 514.52**	2/ 561.43	**3/ 360.2 [12]**
C205	**2/ 793.00**	2/ 950.90	**2/ 780.91**	2/ 958.59	**2/ 740.88**	2/ 922.56	**3/ 360.2 [12]**
R101	12/ 1058.65	12/ 1244.89	12/ 1055.56	12/ 1202.06	12/1096.30	12/ 1209.51	**12/ 1044 [11]**
R201	**3/ 1229.78**	3/ 1440.08	**3/ 1169.20**	3/ 1426.84	**3/ 1217.27**	3/ 1368.65	**6/ 791.9 [10]**
R202	**3/ 1181.61** **4/ 1074.41**	3/ 1282.16	**3/ 1229.69** **4/ 1087.02**	3/ 1254.81	**3/ 1209.41**	3/ 1307.59	**5/ 698.5 [10]**
R203	**3/ 1242.34** **4/ 1022.13**	4/ 1212.08	**3/ 1138.23** **4/ 1046.72**	4/ 1245.69	**3/ 1228.47**	3/ 1470.93	**5/ 605.3 [4]**
R206	**3/ 1044.94**	3/ 1280.41	**3/ 1061.60**	3/ 1285.88	**3/ 936.45**	3/ 1206.01	**4/ 632.4 [4]**
R209	**3/ 1051.73**	3/ 1260.82	**3/ 1121.36**	3/ 1312.52	**3/ 1113.47**	3/ 1256.93	**4/ 600.6 [10]**
RC101	8/ 977.51	10/ 1105.44	8/ 974.70	10/ 1105.96	8/ 982.62	10/ 1098.56	**8/ 944 [11]**

TABLE 3: COMPARISON OF BEST KNOWN RESULTS WITH THE RESULTS GENERATED BY PROPOSED GENETIC ALGORITHMS FOR SOLOMON'S 100 CUSTOMERS SET PROBLEM.

Problem	**DR**		**RD**		**WM**		**Best Known [Ref.]**
	Best	***Worst***	***Best***	***Worst***	***Best***	***Worst***	
C101	10/ 829.70	13/ 1025.76	**10/ 828.94**	12/ 1194.02	**10/ 828.94**	11/ 1095.21	**10/ 828.94 [16]**
R101	20/ 1736.6	21/ 1901.16	20/ 1733.9	21/ 1928.30	20/ 1747.22	21/ 1831.87	**19/ 1650.8 [16]**
R102	18/ 1677.4	20/ 1846.80	18/ 1681.97	20/ 1805.05	18/ 1685.79	20/ 1818.68	**17/ 1486.12[16]**
R105	17/ 1539.5	18/ 1858.66	17/ 1535.08	18/ 1783.36	17/ 1539.5	18/ 1919.20	**14/ 1377.11[18]**
RC101	15/ 1717.31	19/ 2009.08	15/ 1720.82	18/ 1970.63	15/ **1630.09**	19/ 2019.50	**14/ 1696.94[20]**

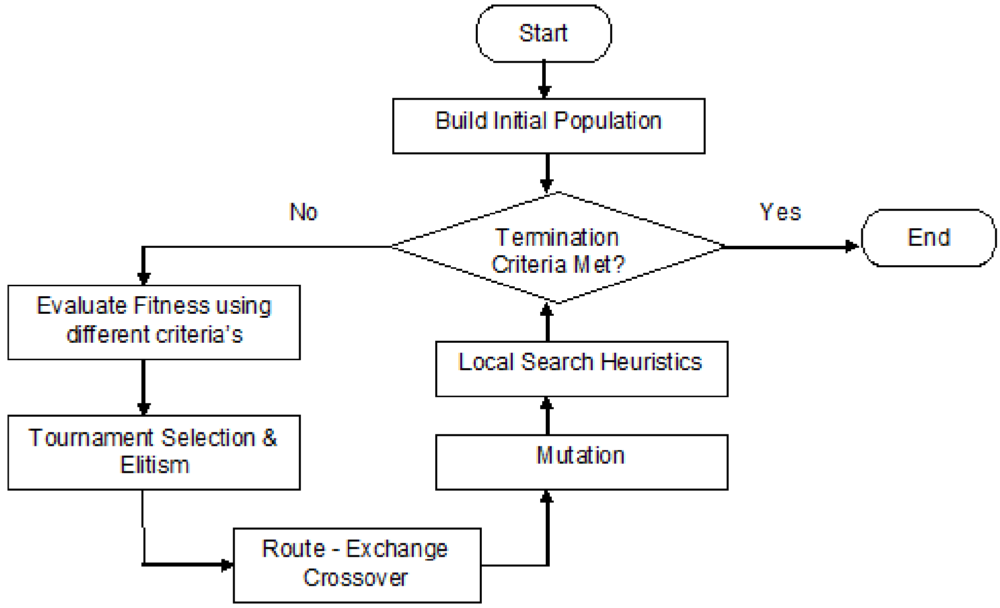

Figure 2. Flowchart of proposed Algorithm

like in R102 and R105 for 100 node problem results are within (15%) of best-known results. In some cases like RC206, R202 and R203 there are two reported solutions in the Table 1 and Table 2 which have lesser number of vehicles than the best-known with higher routing cost.

IV. CONCLUDING REMARKS

Vehicle routing problem with time windows involves the optimization of routes for multiple vehicles so as to meet all constraints and to minimize the number of vehicles needed and total distance traveled. The proposed hybrid algorithm incorporates GA approach with new heuristics in local search. Performance of proposed algorithms is comparable to those available in literature and in some cases even better in terms of number of vehicles which means less fuel, manpower and vehicle maintenance cost with more distance to travel. As for future work, it may be interesting to test proposed algorithm on some application of VRPTW.

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